Soil moisture data assimilation and parameter estimation with EnKF and PF at the TERENO-site Rollesbroich in two models

H. Zhang[1], H. J. Hendricks Franssen[1] , X. Han[1] and H. Vereecken[1]

[1] Forschungszentrum Jülich, Agrosphere (IBG 3), Jülich, Germany

E-mail: ho.zhang@fz-juelich.de

INTRODUCTION

- At the 27ha large TERENO site Rollesbroich in the German Eifel 87 soil moisture time series are b eing recorded. An areal average for 5cm, 20cm and 50cm depth was calculated.
- This dataset is used to test different combinations of data assimilation (DA) algorithms and land surface models.
- Two variants of Ensemble Kalman Filter (EnKF) and Particle Filter (PF) are compared.
- For EnKF state augmentation (Chen and Zhang, 2006) and the dual approach (Moradkhani et al., 2005a) are compared for joint state and parameter estimation.
- For PF the sequential importance resampling Particle Filter (SIR-PF) (Moradkhani et al., 2005b) and the Markov chain Monte Carlo particle filter (McMC-PF) (Vrugt et al., 2013) are tested and compared.
- The DA-algorithms are tested in combination with the land surface models VIC (Liang et al., 1994) and CLM (Oleson et al., 2013).
- Assimilation/calibration period is the first half of 2012, verification period is the second half of 2012.

ROLLESBROICH SITE

The Rollesbroich site is a small catchment in the TERENO Rur catchment. The Rollesbroich catchment has grassland as land use. At the site an eddy covariance station, a soil moisture and soil temperature sensor network (with measurements at 5, 20 and 50cm depth) and a cosmic ray probe are installed. Also soil CO_2 flux measurements and runoff and solute monitoring are carried out, amongst others.

MODEL

The assimilation experiments were carried out with the Variable Infiltration Capacity model (VIC) and Community Land Model (CLM). The main differences between VIC and CLM:

- The soil hydraulic parameters like saturated hydrologic conductivity Ks and soil thermal parameters are the direct input parameters in VIC. For CLM, on the contrary, most of these parameters are calculated by model internal pedotransfer functions as function of soil texture and soil organic matter density.
- Depths of the three soil layers are defined by users in VIC, while in CLM, the thicknesses of the 15 soil layers are internally defined. All the calculations are based on these thicknesses.
- In VIC, the unsaturated and saturated zones are treated in a lumped sense and the impact of groundwater is not taken into account. In CLM, the interaction between the unsaturated zone and the aquifer is included. The change of the groundwater table depth is calculated and included as boundary conditions for solving flow in the unsaturated zone.

EXPERIMENT SETUP

VIC and CLM were spun-up from 1 January 2011 to 31 December 2011. In the first half year of 2012, which was the assimilation period, soil moisture observations at three depths were assimilated. Parameters were also updated in most of the simulation scenarios (Table 1). The second half of 2012 was verification period, in which models ran as the model open loop run but with updated ensembles of parameters from the assimilation part. The assimilation frequency was 24 hours. Table 1 shows different scenarios. In every scenario 100 ensemble members or particles of parameters were generated, see table 2.

scenarios description	Abbr.
Model open loop	openloop
EnKF with invariable parameters	noParamUpdate
EnKF using augmentation	AUG
AUG excluding model error	AUGnoME
EnKF using dual estimation	DUAL
DUAL excluding model error	DUALnoME
SIR-PF	PF
SIR-PF excluding model error	PFnoME
McMC-PF	MCMC

Tab. 1 scenarios used in experiments and their abbreviations

		variables	unit	magnitude
forcing error		precipitation	mm	*(1+0.1*N(0,1))
Param-eter error	For VIC	$\log_{10}$Ks	mm/day	+ N(0,1)
		clay%	fraction	* U[0.8,1.2]
		sand%	fraction	* U[0.8,1.2]
		porosity	fraction	* U[0.8,1.2]
		maximum baseflow velocity	mm/day	~ U[2,20]
		expt	exponent	* U[0.8,1.2]
	For CLM	clay %	fraction	* U[0.8,1.2]
		sand%	fraction	* U[0.8,1.2]
		organic matter density	fraction	* U[0.8,1.2]
Model error		model error	m^3/m^3	~N(0,0.02)
Obs. error		observation error	m^3/m^3	~N(0,0.02)

Tab. 2 Applied parameter perturbations, N indicates normal distribution, U indicates uniform distribution, *, + and ~ mean multiplied, additive and resampled from, respectively.

RESULTS

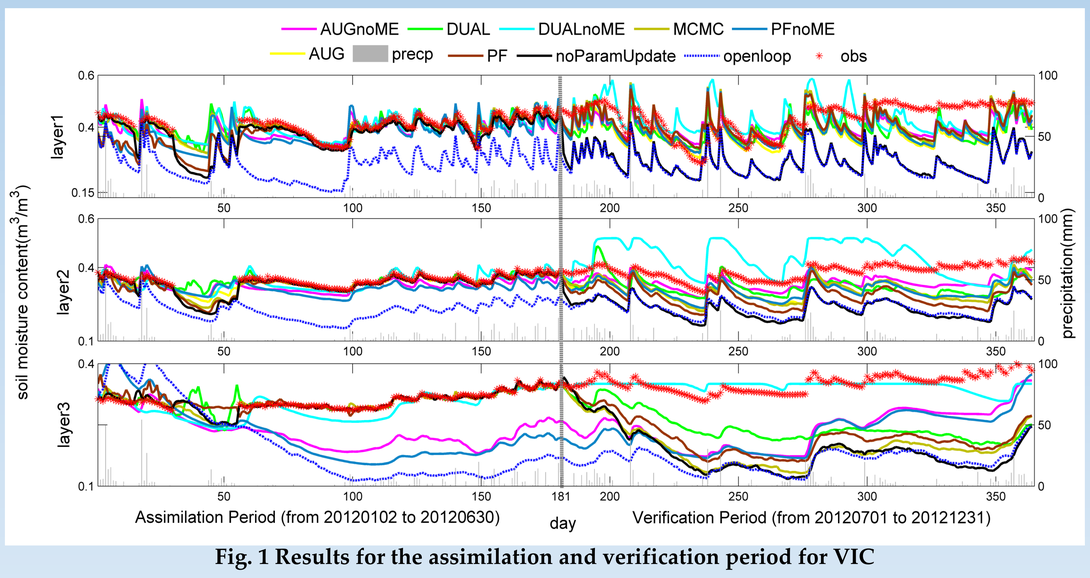

Fig. 1 Results for the assimilation and verification period for VIC

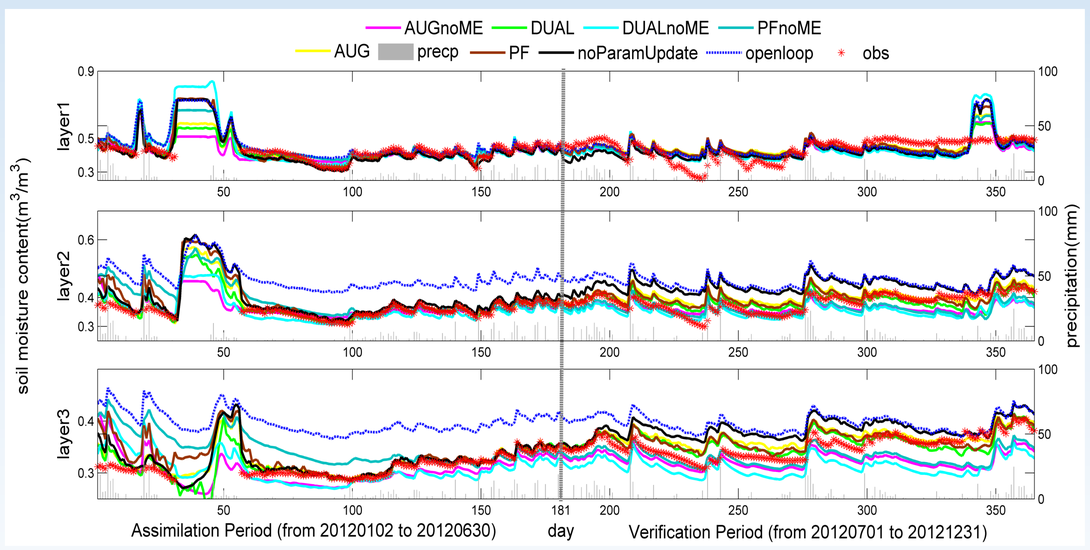

Fig. 2 Results for the assimilation and verification period for CLM

Scenarios	Verification period for VIC			Verification period for CLM		
	Layer1	Layer2	Layer3	Layer1	Layer2	Layer3
AUG	0.0808	0.0810	0.1572	0.0609	0.0322	0.0210
AUGnoME	0.0666	0.0493	0.1162	0.0609	0.0332	0.0322
DUAL	0.0774	0.0715	0.1139	0.0569	0.0262	0.0176
DUALnoME	0.0728	0.0872	0.0257	0.0794	0.0390	0.0432
PF	0.0674	0.1071	0.1372	0.0657	0.0287	0.0181
PFnoME	0.0765	0.0795	0.1253	0.0604	0.0334	0.0273
MCMC	0.0692	0.0818	0.1600			
noParamUpdate	0.1809	0.1540	0.1733	0.0712	0.0648	0.0356
openloop	0.1848	0.1484	0.1893	0.0690	0.0773	0.0472

Tab. 3 RMSE (m^3/m^3) of simulation results in verification period for all scenarios for VIC and CLM, blue values indicate better results and red values worse results

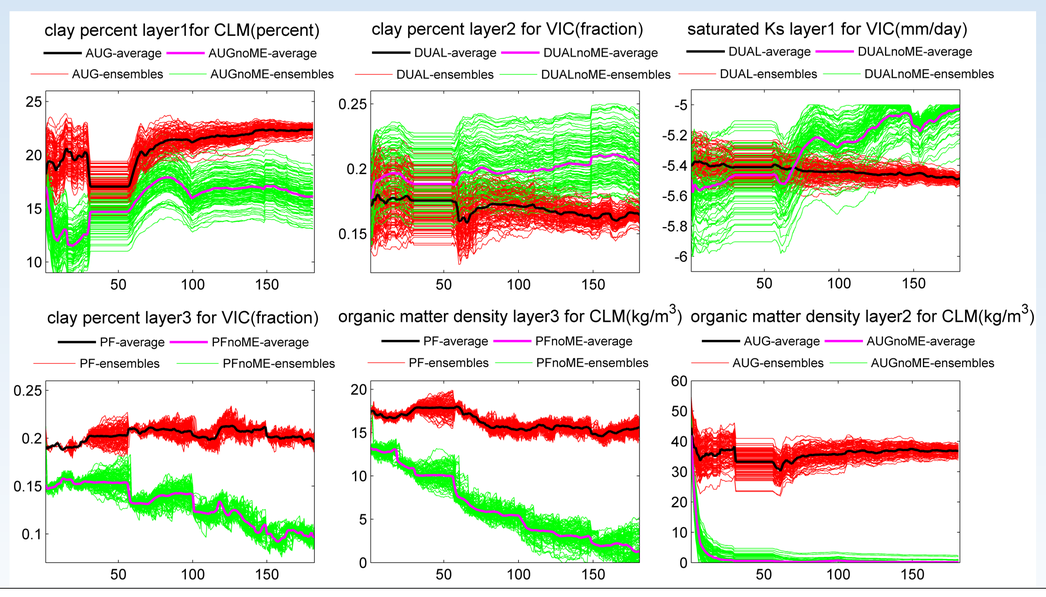

Fig. 3 Ensemble evolution over the assimilation period for the scenarios with parameter estimation, red line corresponds to ensemble of the scenario with model error, while the green line corresponds to an ensemble of the scenario without model error. The black line corresponds to the ensemble average with model error and the pink line corresponds to the ensemble average without considering model error.

CONCLUSION

- all DA algorithms performed well in the assimilation period as the assimilated results were close to the observations.
- In the verification period, the importance of parameter estimation for better characterization of model states became evident. The differences between the four DA-algorithms were not very large.
- It was essential to consider model error in the simulations, as the temporal evolution of parameter values was more realistic if model error was considered (Figure 3).
- The simulation results by VIC for layer 3 indicated lower soil moisture contents than observed, related to the worse representation of groundwater in this model.

REFERENCE

Chen, Y., and Zhang D. X. (2006). Data assimilation for transient flow in geologic formations via ensemble kalman filter. Advances in Water Resources, 29(8), 1107-1122.

Liang, X., Lettenmaier, D. P., Wood, E. F., & Burges, S. J. (1994). A simple hydrologically based model of land-surface water and energy fluxes for general-circulation models. Journal of Geophysical Research-Atmospheres, 99(D7), 14415-14428. doi: 10.1029/94jd00483.

Moradkhani, H., Sorooshian, S., Gupta, H. V., and Houser, P. R. (2005a). Dual state-parameter estimation of hydrological models using ensemble Kalman filter. Advances in Water Resources, 28(2), 135-147. doi:10.1016/j.advwatres.2004.09.002.

Moradkhani, H., Hsu, K., Gupta, H., and Sorooshian, S., (2005b), Uncertainty assessment of hydrologic model states and parameters: Sequential data assimilation using the particle filter, Water Resource Research, 41(5), W05012.

Oleson, K., Lawrence, D. M., Bonan, G. B., Drewniak, B., Huang, M., Koven, C. D., Yang, L., (2013). Technical description of version 4.5 of the Community Land Model (CLM). NCAR Technical Note NCAR/TN-503+STR, 422. doi: 10.5065/D6RR1W7M.

Vrugt, J. A., ter Braak, C. J. F., Diks, C. G. H., and Schoups, G. (2013). Hydrologic data assimilation using particle Markov chain Monte Carlo simulation: Theory, concepts and applications. Advances in Water Resources, 51, 457-478. doi: 10.1016/j.advwatres.2012.04.002.

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